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Review

Riverside Landslide Susceptibility Overview: Leveraging Artificial Neural Networks and Machine Learning in Accordance with the United Nations (UN) Sustainable Development Goals

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Abstract: Riverside landslides present a significant geohazard globally, posing threats to infrastructure and human lives. In line with the United Nations' Sustainable Development Goals (SDGs), which aim to address global challenges, professionals in the field have developed diverse methodologies to analyze, assess, and predict the occurrence of landslides, including quantitative, qualitative, and semi-quantitative approaches. With the advent of computer programs, quantitative techniques have gained prominence, with computational intelligence and knowledge-based methods like artificial neural networks (ANNs) achieving remarkable success in landslide susceptibility assessments. This article offers a comprehensive review of the literature concerning the utilization of ANNs for landslide susceptibility assessment, focusing specifically on riverside areas, in alignment with the SDGs. Through a systematic search and analysis of various references, it has become evident that ANNs have emerged as the preferred method for these assessments, surpassing traditional approaches. The application of ANNs aligns with the SDGs, particularly Goal 11: Sustainable Cities and Communities, which emphasizes the importance of inclusive, safe, resilient, and sustainable urban environments. By effectively assessing riverside landslide susceptibility using ANNs, communities can better manage risks and enhance the resilience of cities and communities to geohazards. While the number of ANN-based studies in landslide susceptibility modeling has grown in recent years, the overarching objective remains consistent: researchers strive to develop more accurate and detailed procedures. By leveraging the power of ANNs and incorporating relevant SDGs, this survey focuses on the most commonly employed neural network methods for riverside landslide susceptibility mapping, contributing to the overall SDG agenda of promoting sustainable development, resilience, and disaster risk reduction. Through the integration of ANNs in riverside landslide susceptibility assessments, in line with the SDGs, this review aims to advance our knowledge and understanding of this field. By providing insights into the effectiveness of ANNs and their alignment with the SDGs, this research contributes to the development of improved risk management strategies, sustainable urban planning, and resilient communities in the face of riverside landslides.

Keywords: riverside landslides; United Nations' Sustainable Development Goals; geo-hazards; artificial neural networks

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1. Introduction

Landslides refer to the non-dense to dense movement of sedimentary layers on a slope that have become unstable (due to different reasons, such as earthquakes, rains, climatic changes, weathering, hydrological changes, subsidence, lack of vegetation, glacial and human activities, etc.) leading to massive movements downstream of the slopes, especially in mountain regions [1,2]. This downward movement in a landslide may occur very slowly, but can occur quickly and leave disastrous effects [3]. The term 'landslide' encompasses five different types of slope instabilities in large scales concluded falls, slides, topples, lateral spreads, and flows. These are further subdivided according to the type of geologic material (rock, debris, snow, ice, or complex). Debris flows (commonly referred to as mudflows or mudslides) and rock falls are examples of common landslide types in mountain areas. Landslides can even occur on seabeds underwater, which creates tidal waves that cause destruction in coastal areas [4]. Schuster [5] stated that landslides are expected to continue in the future due to the increase in urbanization and unplanned development, which leads landslide-prone areas. Landslides cause many human and financial losses to countries every year, which has led to their recognition as the second-most noteworthy type of geological disaster as identified by the United Nations Development Program. So, landslide susceptibility studies are necessary for safer strategic planning of future development activities in landslide-prone areas. Due to the fact that it is very difficult to predict the time of landslide occurrence, it is very important to identify areas sensitive to landslides and to zone these areas based on potential risk. Thus, landslide-prone areas should be identified in order to reduce the damage caused by landslides [6,7]. The main purpose of landslide susceptibility analysis is to identify high-risk areas and, as a result, reduce the damage caused by landslides through appropriate measures. This involves the development of caution frameworks (alarm systems) and land-use management regulations to minimize the loss of damages [8].

In landslide occurrences, there are several factors that provide suitable conditions for landslides to be triggered due to failures. These factors are known as 'triggering' or 'conditioning' factors and are responsible for ground movements of different scales, which can be classified into internal and external factors [9]. Internal factors of landslide formation are related to soil and rock materials, including soft and weak rock properties or rock strata with multiple joints or shear fracture zones, as well as geological structure, topography, vegetation, microelectronics, etc. External factors include weathering; increased pore water pressure; increased loading; flourish vegetation; the reduced supporting forces of toe; erosion; snowmelt; changes in water level; the collapse of underlying strata; lateral pressure; the freezing process; earthquakes; volcanic activity; disturbance due to human activities; unplanned construction; land-use change; and vibrations and torrential rains [10]. Highland and Bobrowsky [11] categorized the factors triggering landslides into seven main classes, which are used by researchers in susceptibility assessments. These factors are climatologic, geomorphologic, geologic, geostructural, seismic, geohazard-triggered, landslide-prone areas, and men's work. Some of these factors may be dominant in some areas, and some may be weak. But in a proper sensitivity analysis, paying attention to all aspects of the evaluation can provide a more appropriate and accurate view.

Landslide susceptibility and monitoring analyzes the probability of landslide occurrence at different local, regional, and national levels using certain conditional factors [12,13]. Each level of analysis requires a specific range of data, software and hardware availability, user experiences, and strong interpretations [14]. As is known, landslides cause drastic changes to landscape morphology and reduce land production [15]. Most of these events occur on cut-slopes or in embankments along roads and highways in mountainous areas, while some major failures occur in residential areas near ground modifications or where there is improper land-use change [16,17]. Landslides are the result of spatiotemporal processes and are actually influenced by main and momentary variables. The main variables include bedrock geology, soil conditions (soil type and depth), morphology, topography (angle, aspect, curvature, topology), land-use/land-cover, drainage networks, vegetation, etc. Momentary variables include also heavy rains, earthquakes, and volcanic activity [18–21]. It is expected that this trend will continue in the coming decades due to the increase in urbanization and development, the continuation of deforestation, and the increase in regional rainfall in areas prone to landslides due to the change in climatic patterns [22–24]. Thus, identifying landslide-prone areas is essential for safer strategic planning of future development activities in various regions [25–27]. Over the decades, landslide sensitivity and risk assessment have been increasing [28]. Landslide susceptibility modeling is generally divided into two main groups: qualitative and quantitative approaches. In general, a qualitative approach is based on the subjective judgment of an expert or a group of experts, while a quantitative approach is based on a mathematically rigorous objective methodology [29]. In recent decades, the use of landslide vulnerability and risk maps for land use planning has increased significantly. These maps rank different parts of the land surface according to the actual or potential risk of landslides. Therefore, planners are able to choose the best places for urban and rural development [30,31]. Figure 1 provides a risk variation flowchart regarding landslide susceptibility assessment which was developed based on various levels of analysis.

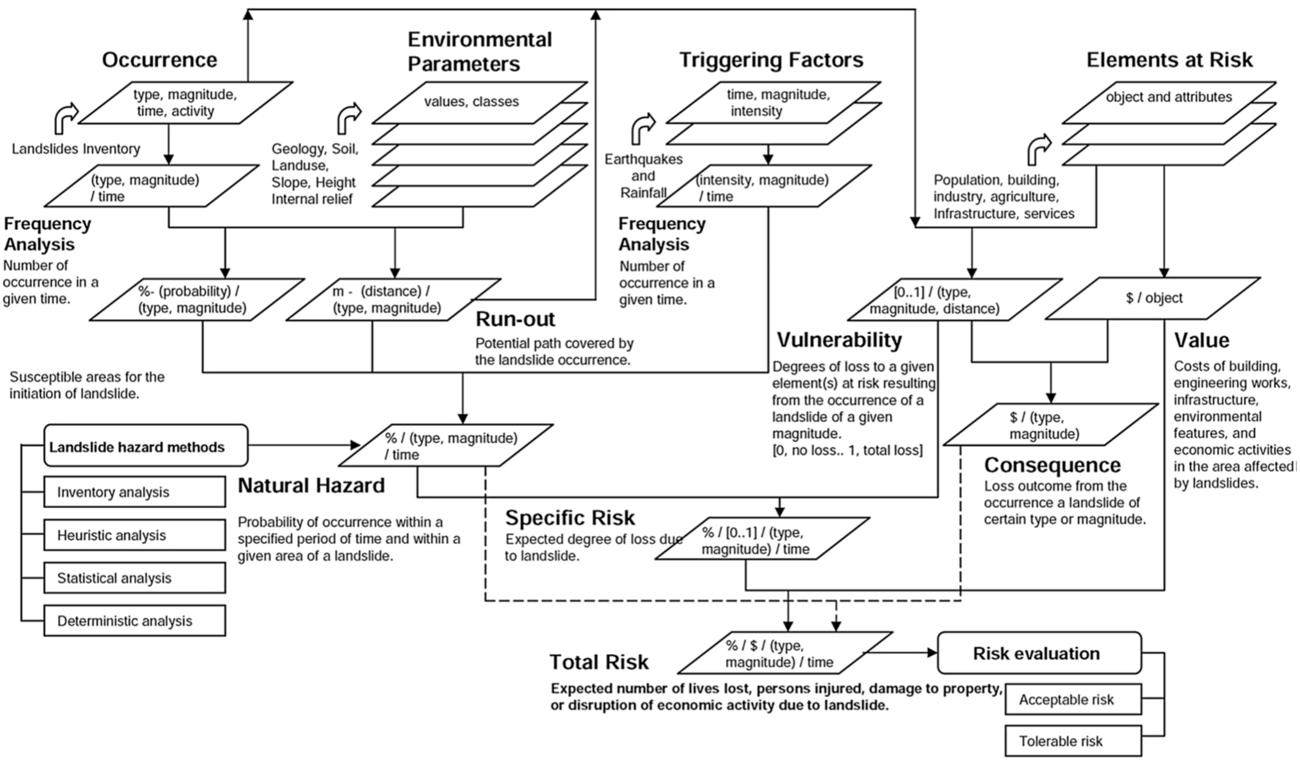

Figure 1. The landslide risk assessment framework (adapted from Ref. [32]).

Various triggering factors, such as geological conditions, hydrological and hydrogeological anomalies, topographical and morphological status, climate, weathering effects, seismicity, and human activity, impact the stability of a slope and can cause landslides [33–38]. Although the amount of damage caused by landslides is higher in developed countries, according to the studies conducted by the Center for Natural Disasters of the United Nations, for many developing countries, these damages are one and two percent of production, which is their national gross value [39]. From one perspective, the causes of landslides can be divided into the following two groups: (i) natural triggering factors, including geological factors and morphological factors, which can be caused by sensitive or poorly weathered materials; the presence of cut, seamed, or cracked materials; discontinuity with the opposite direction (layering, schistosity, fault, contact surface, etc.); differences in the permeability or hardness of materials; morphological factors caused by technological or volcanic activities; removal of pressure caused by melting glaciers, river erosion, waves, or frost at the foot of the slope or its side margins; underground erosion (dissolution of boiling); sediment loading on the slope or above it; removal of vegetation (due to fire or drought); melting of snow; weathering caused by freezing or melting; and weathering due to contraction and expansion. The second category (ii) comprises human triggering factors such as digging on the slope or loading on the slope or above it; drops in the underground water level; cutting of forest trees; irrigation; mining; artificial seismic fluctuations, and water subsidence from facilities [40]. However, these elements are only a few examples of the factors that can contribute to landslides. There are numerous other causes that can trigger landslides. Therefore, it is essential to conduct mapping exercises to accurately zone areas prone to landslides [31]. The determining factors involved in landslide occurrence include the following [33–38].

Geological: The geology of any region has a substantial effect on the mass movement that occurs there. The region's physical constitution and elements are among the geological considerations. Numerous social networking sites offer geology maps for various countries that can be digitized in order to map the geology of any study area.

Topographical: In reference to the elevation, topographical elements include slope, slope aspect (direction of slope), plan curvature, and profile curvature. GIS can be used to map topographical features using the digital elevation model (DEM) derived from Cartosat-1, Sentinel-1, and Sentinel-2 satellite images received through USGS EarthExplorer.

Hydrological: Rainfall is one of the most factors influencing landslides in hilly locations; therefore, its examination is required for landslide zonation mapping. For rainfall mapping, at least the ten-year average must be considered. The Climatic Research Unit (CRU) provides rainfall information for all regions. Other elements, such as drainage density, flow direction, and watersheds, also contribute to the occurrence of landslides. These characteristics are mapped using the DEM provided for the studied region.

Land coverage: Land-use and land-cover (LULC) are used to provide an understanding of the existing landscape. Due to increased land usage in hilly regions, the surfaces of hills are becoming disturbed, resulting in a rise in landslides. Thus, mapping of LULC is essential for analyzing the annual data from national databases, which enable us to monitor the temporal dynamics of agriculture, forest conservation, surface water bodies, etc., on an annual basis. Landsat images for a specific region can be obtained through USGS EarthExplorer using Landsat TM. Supervised classification can then be used in GIS to map and validate every feature using Google Earth Pro or a base map for that region.

Geotechnical: The predominant failure mode of soil is shear, making the soil type a crucial factor in landslides. A critical element of landslide research is estimating the slope's stability and offering appropriate alternatives. Most of these studies are carried out by conducting a complete geotechnical investigation of the landslide, collecting soil samples from the landslide location, analyzing its specific physical features, and estimating its stability factor. These results are then utilized to develop a 2D model of the slope stability of the region.

Susceptibility assessments use various quantitative, qualitative, and semi-quantitative procedures to analyze and extract the areas suitable for landslides and to predict where landslides may occur. These are implemented either directly or indirectly [14]. Qualitative approaches are subjective, determining sensitivity heuristically and assessing sensitivity levels using descriptive and qualitative terminology. Quantitative methods produce numerical estimates, or, in other words, the probability of occurrence of landslide phenomena in each susceptibility zone [41]. The other classification categorizes the susceptibility assessments using various approaches, such as deterministic, statistic, heuristic, inventory, geostatistic, and knowledge-based methods [42,43]. Regardless of the type of susceptibility method, all refined methods have been developed based on the principle that the present and the past are the keys to the future, thus enabling fewer subjective analyses to be conducted where landslide susceptibility is assessed by statistical relationships between past landslide events and domain instability factors.

Although the deterministic methods produce definitive results for landslide susceptibility, they are not feasible for large-scale landslide analysis or conditional-based evaluations. Therefore, these methods' application may be performed for medium- to large-scale assessment, along with errors [44]. Statistical procedures use exploration–exploitation of data collected from different triggering factors, which allows for these data to be expanded on various scales via the GIS environment [45], but this expansion is associated with uncertainties and errors [46]. Heuristic and likelihood ratio methods use expert judgments to achieve qualitative assortment of landslides, which involves human error based on user experiences in analysis; this, in some high-impact assessments, is inappropriate [47].

In recent years, landslide susceptibility assessment has undergone significant advancements, incorporating more sophisticated procedures to analyze and predict the likelihood of landslide occurrence in different regions while taking into account various triggering factors. Computer-based programming allows for susceptibility evaluations, reduced errors, and minimized uncertainties, and has received the attention of many professionals worldwide. Computer-based methods are known as knowledge-based approaches, which represent the application of computational intelligence to solve complex problems and detect hazardous areas in terms of landslide occurrences with high accuracy. Knowledge-based approaches like fuzzy logic, machine learning, and artificial neural networks (ANNs), as well as metaheuristic, data-driven, stochastic, data-mining, and adaptive neuro-fuzzy inference system (ANFIS) methods, provide appropriate results for classification and prediction of risk potential for landslide occurrences, and this leads to the development of extraordinary zonation maps with high accuracy in different regions. Thus, recently, utilization of these procedures has been expanding and developing.

The presented article highlights the application of artificial neural networks (ANNs) in landslide susceptibility assessments, showcasing their prominent role as highly recommended and widely used procedures for analyzing susceptibility and mapping hazard risks associated with landslides in riverside areas. The adoption of ANNs in this context stems from their capacity to effectively handle complex and heterogeneous geospatial datasets, enabling the automatic extraction of critical features from remote sensing imagery, LiDAR data, and topographic information. Their ability to discern intricate spatial relationships and patterns contributes to the development of accurate landslide susceptibility models, facilitating proactive hazard management and informed decision making for riverside communities. To provide a comprehensive understanding of this rapidly evolving field, this article undertakes a rigorous review of the relevant literature encompassing recent developments and advancements in landslide susceptibility assessment methodologies. By synthesizing existing research, the authors aim to shed light on the theoretical foundations, methodological approaches, and practical applications of ANNs in riverside landslide susceptibility assessment. The review encompasses studies that have explored the integration of multi-sensor remote sensing data, the fusion of hydrological and geotechnical modeling, and the implementation of advanced deep learning algorithms to enhance the accuracy and efficiency of landslide susceptibility mapping in riverside regions.

Through a comprehensive examination of the literature, this article seeks to unveil the potential of ANNs to revolutionize the field of landslide susceptibility assessment, contributing to the formulation of proactive and effective risk mitigation strategies and supporting the sustainable development of riverside areas. The insights gleaned from this thorough review pave the way for further research endeavors and provide valuable guidance to researchers, practitioners, and policymakers striving to mitigate the adverse impacts of landslides in vulnerable regions. As the body of knowledge in this domain continues to expand, this article will serve as a foundational resource, fostering a deeper appreciation of the pivotal role that ANNs play in advancing our understanding of landslide susceptibility in riverside environments.

2. Early Works on Landslide Susceptibility

Since the mid-1970s, a substantial body of literature has been published on landslide susceptibility, which was often referred to in the early literature as a ‘hazard’ concept for landslides. These studies examined the functional relationships between the geographic distribution of landslides and geoenvironmental factors that trigger landslides to occur.

They used different deterministic–statistic approaches implemented at different genetic scales and adopted a variety of mapping units. Neuland [48] was likely the first to use a statistical approach to explain the relationships between morphometric, geomechanical, lithological, and structural characteristics in order to construct a specific stability–instability prediction model for a landslide. A few years later, Carrara [49] summarized the results of a long-term effort aimed at understanding the geological and morphological factors controlling landslides in Calabria, southern Italy. He used multivariate analysis (discriminant and multiple regression analysis) methods to predict landslide susceptibility based on a large set of landslide-related, geological, and geomorphological data. Carrara and colleagues developed specially designed software for automated mapping of distributed slippage and genetic environmental information; these were early versions of the original geographic information systems (GIS) based on neural networks [50]. Yin and Yan [51] analyzed 21 different triggering factors based on data collected from field surveys and remote-sensing for landslide mapping. Rib and Liang [52], Varnes [53], Hutchinson [54], and Dikau et al. [55] conducted various studies on landslides with distinct geomorphological features using field surveys and remote sensing image interpretations. These works provide the principles of landslide susceptibility assessments that have been mentioned in the last decade. Aleotti et al. [56] classified the triggering factors based on data availability and the scale of the studied region to improve landslide susceptibility mapping. Aleotti and Chowdhury [57] provided susceptibility maps based on identifying the causative factors and categorizing the historical data related to landslide occurrences, as well as the number of obstacles that may be faced while producing landslide hazard maps.

3. Riverside Landslides

Riverside landslides refer to the occurrence of landslides in areas adjacent to rivers or other bodies of water. These types of landslides can occur along riverbanks, slopes near river channels, or even within river valleys. Riverside landslides can be triggered by various factors, including natural causes such as heavy rainfall, rapid erosion of riverbanks, or changes in river water levels. Human activities such as construction, deforestation, and improper land management can also contribute to the occurrence of riverside landslides [12,13,20,25]. The presence of water in riverside areas plays a significant role in influencing slope stability. Water can infiltrate the soil, increasing its pore pressure and reducing the frictional strength of the soil particles, making the slopes more prone to failure. Additionally, river currents can erode the bases of slopes, further compromising their stability [27,28].

Riverside landslides pose significant risks to infrastructure, communities, and ecosystems. They can result in the destruction of buildings, roads, and bridges, leading to economic losses and potential loss of life. Furthermore, landslides in riverside areas can block river channels, causing floods and altering the course of rivers [34–37].

Riverside landslide susceptibility refers to the likelihood of landslides occurring in areas adjacent to rivers or bodies of water. Several factors contribute to the susceptibility of riverside landslides. Steep slopes, geological composition, and weak soil types are key factors that increase vulnerability. Hydrological factors such as heavy rainfall, high groundwater levels, and fluctuating river water levels also play a significant role. Human activities like construction, deforestation, and improper land management can further exacerbate susceptibility. Assessing riverside landslide susceptibility involves field investigations, geological surveys, and slope stability analysis. Advanced techniques such as remote sensing, GIS, and machine learning algorithms like ANNs offer new opportunities for more accurate and comprehensive landslide susceptibility mapping [25–29].

Understanding riverside landslide susceptibility is essential for effective risk management and land-use planning [13]. Integrating various data sources, such as geological, topographical, hydrological, and vegetation information, allows for the identification of patterns and relationships that contribute to landslide occurrences [47]. By analyzing complex datasets using machine learning algorithms, professionals can develop predictive models and susceptibility maps that help to identify areas at higher risk [30–32]. This knowledge enables the implementation of appropriate measures to mitigate the potential impact of landslides on riverside communities, infrastructure, and ecosystems. Improved understanding of riverside landslide susceptibility can inform early-warning systems and guide decision-making processes related to development and land-use practices in vulnerable areas, ultimately reducing the potential risks associated with landslides [42,43].

Table 1 provides a comprehensive overview of factors contributing to high-risk riverside landslide susceptibility. These factors encompass various geological, hydrological, and human-related aspects that significantly influence the stability of slopes adjacent to rivers. Understanding these factors is vital for assessing and mitigating landslide hazards in riverside areas [25]. Steep slopes pose a substantial risk, as higher slope angles increase the potential for slope failure. Weak geological compositions, such as weathered or fractured rock layers, contribute to instability and compromise slope strength. Similarly, the presence of unstable soil types, including loose sands, silts, and clays, increases the vulnerability to landslides [3,6,12–16]. Hydrological factors play a crucial role, with heavy rainfall being a primary trigger for riverside landslides. Intense or prolonged precipitation saturates the soil, leading to increased pore water pressure and reduced soil strength. High groundwater levels and fluctuating river water levels also influence slope stability and contribute to increased susceptibility [40–43]. Deforestation removes the stabilizing effect of vegetation, weakening the slopes and promoting erosion. Improper land management, such as inadequate drainage systems or modifications to natural drainage patterns, further compromises slope stability. Additionally, construction activities, especially without proper slope stabilization measures, can trigger landslides [38].

Table 1. Factors contributing to high-risk riverside landslide susceptibility.

Triggering Factors	Description
Steep slopes	High slope angles increase the potential for slope failure.
Weak geological composition	The presence of weak or weathered rock layers increases instability.
Unstable soil types	Loose sands, silts, and clays are prone to landslides.
Heavy rainfall	Intense or prolonged precipitation saturates the soil, leading to increased pore water pressure and reduced soil strength.
High groundwater levels	Elevated groundwater levels increase the likelihood of landslides.
Fluctuating river water levels	Variations in river water levels can impact slope stability.
Deforestation	Removal of vegetation weakens slopes and increases erosion.
Improper land management	Inadequate drainage systems or modifications of natural drainage patterns can contribute to instability.
Construction activities	Excavation and modification of slopes without proper stabilization measures can trigger landslides.
Seismic activity	Earthquakes can induce landslides in riverside areas.
Riverbank erosion	Rapid erosion of riverbanks weakens slopes and increases the likelihood of landslides.
Climate change effects	Changing rainfall patterns and increased weather extremes can affect landslide susceptibility.
Human settlement density	High population density in riverside areas increases exposure and vulnerability to landslides.
Land-use changes	Alterations in land use, such as urbanization or agriculture, can impact slope stability.
Geomorphic features	Presence of natural depressions, river meanders, or concave slopes can contribute to instability.
Underground water flow	Subsurface water flow patterns can affect slope stability in riverside areas.
Slope disturbances	Excavations, cut slopes, or fillings can alter the natural equilibrium of slopes.
Geological faults and fractures	Active faults or fractures can enhance the susceptibility of riverside slopes to landslides.

Understanding these high-risk factors is essential for effective landslide hazard assessment and developing appropriate mitigation strategies. By considering these factors, professionals can implement targeted measures to reduce the potential impact of landslides on riverside communities, infrastructure, and ecosystems. To assess and mitigate the risks associated with riverside landslides, researchers and professionals employ various techniques, including geotechnical investigations, remote sensing, and numerical modeling. The ANNs and machine learning (ML) algorithms have gained prominence in recent years for landslide susceptibility assessment, offering the ability to analyze complex datasets and identify patterns that can help to predict landslide-prone areas alongside riverbanks. Understanding the factors that contribute to riverside landslides and developing accurate susceptibility mapping techniques are crucial for effective risk management, land-use planning, and the implementation of appropriate mitigation measures in these vulnerable areas [49,50].

In recent years, several innovative techniques have emerged in riverside landslide susceptibility assessment. Integrating multi-sensor remote sensing data, such as optical imagery, synthetic aperture radar (SAR), and LiDAR, allows for a comprehensive understanding of terrain features and land cover changes, leading to more accurate identification of landslide-prone areas over time [6,9]. Machine learning and artificial intelligence methods, such as convolutional neural networks (CNNs) [54], have proven to be effective at automatically extracting relevant features from geospatial data, resulting in improved landslide susceptibility mapping in riverside regions [30]. Moreover, the incorporation of hydrological and geotechnical modeling provides valuable insights into the impact of water movement and soil properties on slope stability, aiding in the formulation of effective mitigation strategies. Additionally, InSAR (Interferometric Synthetic Aperture Radar) technology has demonstrated high precision in terms of monitoring ground surface displacements, allowing for real-time monitoring of dynamic slope behavior in riverside areas, which is essential for early-warning systems and risk assessment. These advancements have collectively enhanced the accuracy and efficiency of riverside landslide susceptibility assessment, and are paving the way for informed decision-making and sustainable land use planning in high-risk zones [35–41].

Assessing riverside landslide susceptibility offers several advantages for effective risk management and decision making. Firstly, it enables targeted risk management strategies to be developed. By identifying areas with higher susceptibility to landslides, authorities can implement measures such as early-warning systems, land-use planning regulations, and slope stabilization techniques to mitigate the potential impact on communities, infrastructure, and ecosystems. Secondly, it enhances hazard assessment by providing a systematic and scientific approach. By considering factors such as slope characteristics, geological composition, hydrological conditions, and human activities, professionals can gain a comprehensive understanding of landslide risks and prioritize areas for further investigation and mitigation [40–48].

This improves the allocation of resources and efforts towards areas most susceptible to landslides. Lastly, assessment contributes to improved planning and decision making. The knowledge gained from landslide susceptibility assessments can inform land-use planning processes, ensuring that areas less suitable for certain types of development are identified and that appropriate engineering measures are implemented to minimize landslide risks. It also allows for the integration of environmental conservation and sustainable development practices into decision-making processes [50–63].

While assessing riverside landslide susceptibility offers significant benefits, there are also limitations and challenges to consider. One primary challenge is the uncertainty and limitations associated with predicting landslides. The exact timing, magnitude, and location of landslides are difficult to determine due to the complexity of slope processes, variability in environmental conditions, and limitations of data availability and accuracy. Additionally, conducting comprehensive susceptibility assessments requires substantial amounts of data, including geological, topographical, hydrological, and vegetation information. Gathering, organizing, and analyzing such data can be time-consuming and resource-intensive, particularly in large-scale assessments [6,9]. Furthermore, the dynamic nature of susceptibility poses a challenge. Riverside landslide susceptibility is not static and can change over time due to natural and human-induced factors. Changes in climate, land use, or hydrological patterns can alter the susceptibility levels of certain areas, necessitating regular updates and reassessment of landslide susceptibility mapping [64–70].

Despite these challenges, the advantages of assessing riverside landslide susceptibility outweigh the disadvantages. The approach enables the proactive and targeted management of landslide risks, facilitates informed decision-making processes, and contributes to the overall safety and resilience of riverside communities and infrastructure. Continuous advancements in data collection techniques, modeling approaches, and monitoring systems will further enhance the effectiveness and reliability of landslide susceptibility assessments [32].

4. Artificial Neural Nets in Geohazards

4.1. The ANNs Concepts

According to many scientists, the human brain is the most complex system ever observed and studied in the entire universe. But this complex system has neither gigantic dimensions nor the same number of components as the processors of today's supercomputers. The mysterious complexity of this unique system comes from the many connections between its components. This is what distinguishes the human brain from all other systems. The conscious and unconscious processes that occur within the geographical limits of the human body are all under the management of the brain. Some of these processes are so complex that no computer or supercomputer in the world can process them. The very high processing speed and power of the human brain are due to the massive connections that exist among the cells that make up the brain, and basically, without these communication links, the human brain would be reduced to an ordinary system and would definitely not have its current capabilities.

Apart from this, the brain's excellent performance in solving all kinds of problems and its high efficiency have caused simulating the brain and its capabilities to become the most important aspiration of hardware and software architects. In the past few decades, during which computers have made it possible to implement computational algorithms in order to simulate the computational behavior of the human brain, many research works have been undertaken by computer science experts, engineers, and mathematicians, the results of which are in the branch of artificial intelligence science. They are classified in a sub-branch of computational intelligence under the title of 'Artificial Neural Networks (ANN)' [58]. ANNs are computing systems inspired by the biological neural networks that constitute the brain. They which were developed to understand learning using computers operated with a collection of nodes (connected units), called artificial neurons. Each node receives signals and processes them, then sends them to another node for the progressive process [59]. Figure 2 presents a classification of the ANNs that are commonly employed in diverse tasks within the field of geo-engineering. Additionally, Table 2 showcases the successful implementation of various ANN techniques in relevant research studies.

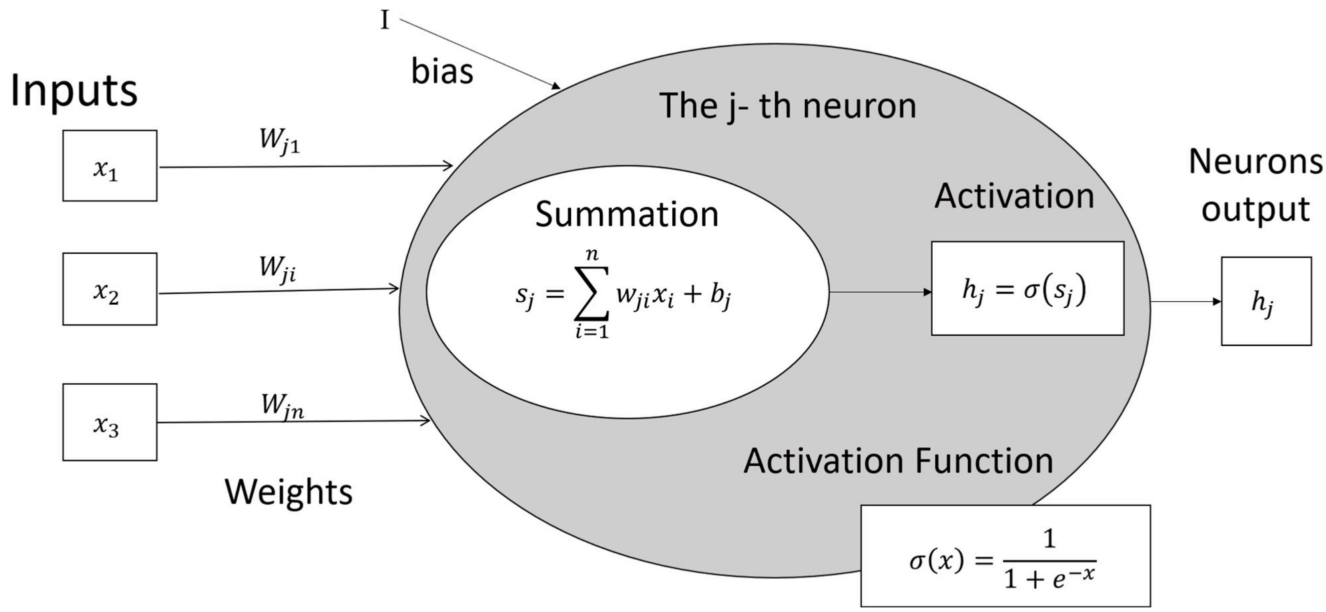

Figure 2. ANN types used in the engineering field (adapted from Ref. [68]).

Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs [68]. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times [69]. Neural networks learn (or are trained) by processing examples, each of which contains a known "input" and "result", and form probability-weighted associations between the two, which are stored within the data structure of the net itself. The training of a neural network from a given example is usually conducted by determining the difference between the processed output of the network (often a prediction) and the target output. The network then adjusts its weighted associations according to a learning rule and uses this error value. Successive adjustments cause the neural network to produce outputs that are increasingly similar to the target output. After a sufficient number of these adjustments, the training can be terminated based on certain criteria [70]. The learning process consists of a collection of simulated neurons. Each neuron is a node that is connected to other nodes via links that correspond to biological axon–synapse–dendrite connections. Each link has a weight that determines the strength of one node's influence on another, which is measured by the learning rate of the ANNs. Learning is the adaptation of the network to better handle a task by considering sample observations. Learning involves adjusting the weights (and optional thresholds) of the network to improve the accuracy of the result. This is conducted by minimizing the observed errors. Learning is complete when examining additional observations does not usefully reduce the error rate. Even after learning, the error rate typically does not reach 0. If, after learning, the error rate is too high, the network typically must be redesigned. Practically, this is accomplished by defining a cost function that is evaluated periodically during learning. As long as its output continues to decline, learning continues. The cost is frequently defined as a statistic whose value can only be approximated [71]. The learning rate defines the size of the corrective steps that the model takes to adjust for errors in each observation [69]. A high learning rate shortens the training time, but achieves lower ultimate accuracy, while a lower learning rate takes longer, but has the potential for greater accuracy. Optimizations such as Quickprop are primarily aimed at speeding up error minimization, while other improvements mainly attempt to increase reliability [70].

Table 2. A summary for recent developments on ANN application in the geo-engineering field.

ANN Method	Advantages	Limitations	References
MLP	Nonlinear modeling, ability to handle large data sets, flexibility, fast computation, generalization to unseen data, adaptability	Limited ability to handle sequential data, limited interpretability, overfitting, limited data efficiency, limited model complexity	[60]
CNNs	Spatial analysis, feature extraction, generalization to new data sets, adaptability, image processing tasks, efficient computation	Limited ability to handle non-image data, difficulty in handling varying input sizes, limited interpretability, limited data efficiency, limited ability to handle extreme events	[61]
RNNs	Time-series analysis, sequential analysis, memory component to remember past events, generalize well to new data sets, adaptability, efficiency	Difficulty in handling long sequences, limited ability to handle non-sequential data, limited interpretability, difficulty in handling variable-length input data, limited data efficiency	[62]
DNNs	Nonlinear modeling, achieves high accuracy in prediction tasks, automatically extracts features from data sets, generalizes well to new data sets, adaptability, efficiency, flexibility	Limited ability to handle rare events, limited interpretability, difficulty in handling imbalanced data	[63]
GNNs	Graph analysis, topological analysis, feature extraction, efficient computation	Difficulty in handling large graphs, limited interpretability, limited ability to handle variable graph sizes, limited data efficiency, limited ability to handle graph heterogeneity	[64]
LSTM	Time-series analysis, nonlinear modeling, memory component to remember past events, generalizes well to new data sets, adaptability, efficiency	Difficulty in handling long sequences, limited interpretability, limited ability to handle variable sequence lengths, limited data efficiency, limited ability to handle non-stationary data	[65]
FFNN	Nonlinear modeling, high accuracy in prediction tasks, interpolation and extrapolation, generalize well to new data sets, adaptability	Limited ability to handle sequential or graph data, limited interpretability, limited ability to handle missing or noisy data, limited ability to handle high-dimensional data, limited ability to handle imbalanced data	[66]
Autoencoders	Data compression, feature extraction, anomaly detection, data denoising, efficiency	Limited interpretability, limited ability to handle sequential or graph data, limited ability to handle high-dimensional data, limited data efficiency	[67]

Machine learning is commonly separated into three main learning paradigms: supervised learning, unsupervised learning, and reinforcement learning. Each type corresponds to a particular task. ANNs are divided into several types and procedures which are able to provide different accuracy levels, classified as shallow and deep learning [72]. The simplest types have one or more static components, including the number of units, number of layers, unit weights, and topology. In complex ANNs, the number of layers and units and the topology become more complicated and extensive. Generally, ANNs are classified into modular neural nets, feed-forward neural nets (e.g., multilayer perceptron, MLP), Kohonen self-organizing neural nets, radial basis function nets, and deep nets. Convolution neural networks (CNNs), recurrent neural networks (RNNs), deep neural networks (DNNs), long short-term memory (LSTM), deep belief nets (DFNs), autoencoders (AEs), generative adversarial nets (DAN), and graph neural nets (GNN) are the most common deep nets utilized by researchers [73]. Figure 3 demonstrates the simple architecture of shallow and deep learning procedures.

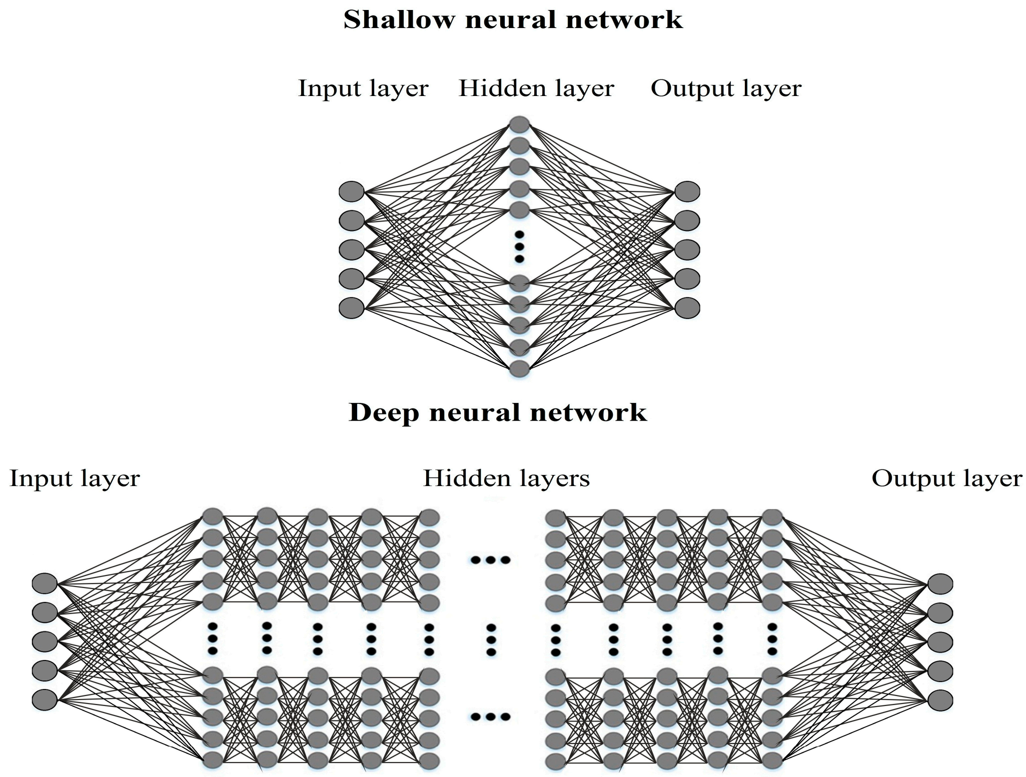

Figure 3. Topical shallow and deep neural network architectures (adapted from Ref. [73]).

Shallow learning in ANN refers to the use of neural networks with only a few hidden layers. Typically, a shallow neural network consists of one or two hidden layers, as opposed to deep neural networks, which can have dozens or even hundreds of hidden layers. This learning can be useful for solving simpler and less complex problems where a lower number of parameters and computations is required [38]. However, for more complex tasks, deep learning models are often required. This is because deep learning models can handle a large number of parameters and computations, allowing them to learn complex patterns and relationships within data [72]. Regardless of the layers and extended structure of neural networks, ANN can be classified into four learning groups, which are presented in Figure 4. On the other hand, using deep learning helps to solve complicated problems. Deep learning can be categorized into various groups, which are illustrated in Figure 5.

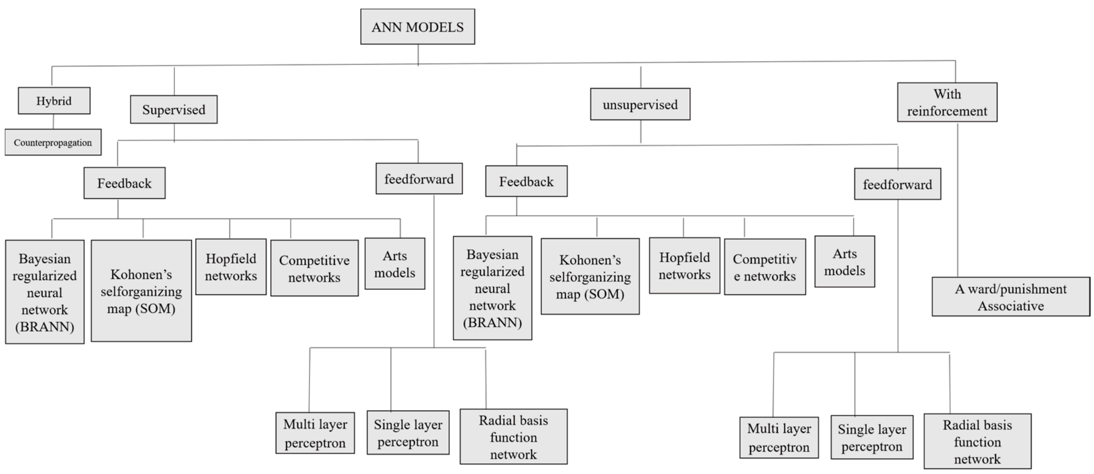

Figure 4. A summary of ANN models used in the engineering field (adapted from Ref. [72]).

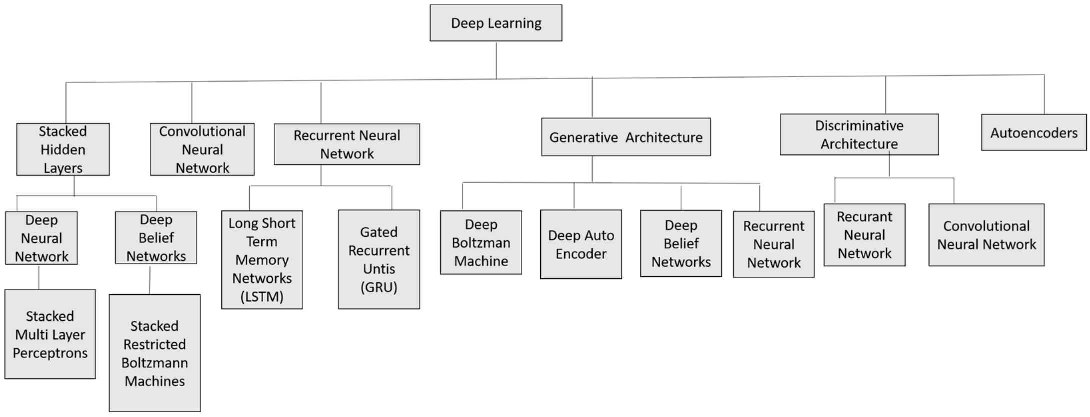

Figure 5. A summary of deep learning models used in the engineering field (adapted from Ref. [73]).

4.2. ANN Capability in Geohazard Assessment

Geohazards are natural disasters or events that result from the earth's geological processes, and they can cause significant damage or harm to humans and the environment. There are several types of geohazards, which are illustrated in Figure 6 [74]. Volcanic eruptions, earthquakes, landslides, tsunamis, sinkholes, etc., are several well-known geohazards [75]. Geohazards can have significant impacts on human societies and the environment, and it is important to take measures to minimize their risks and to be prepared for their occurrence. This can include building infrastructure that is designed to withstand earthquakes or landslides, monitoring volcanoes and other geohazard-prone areas, and developing emergency response plans for tsunamis and other natural disasters [76].

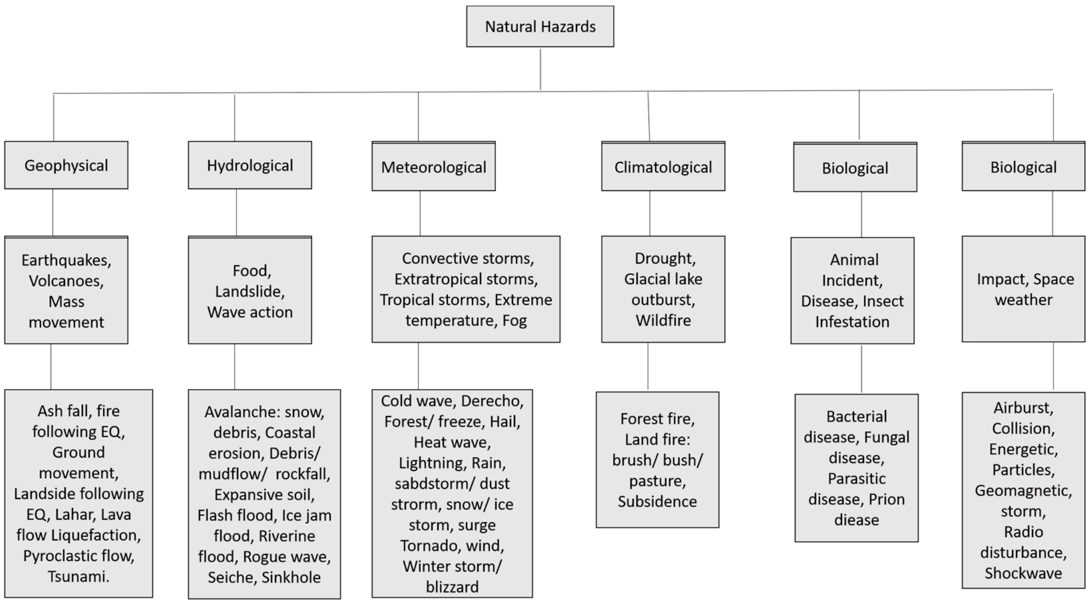

Figure 6. A summary of various geohazard categories (adapted from Ref. [76]).

Artificial neural nets are capable of providing classification and prediction information based on primary databases that are prepared using different types of recordings. The performance of ANNs is directly related to the extension of the primary datasets, which leads to a proper learning rate and prediction with more appropriate accuracy. If the learning rate increases, the model is able to test (predict) with high precision, which leads to more accurate results. The records in geohazards assessments that can be used to prepare the main database are categorized into remote-sensing data, DEM data, unmanned aerial vehicle (UAV) images, geological information, ground surveys, aerial photography, historical events, and other relative data [77].

Remote-sensing data: Satellite images and radar data are used for geohazard susceptibility assessments, which provide their main data from the ground surface before other information is included with these data. Typically, the satellites which collect remote-sensing data include Landsat, Sentinel-1, RapidEye, ALOS, GeoEye, and QuickBird [78]. Each of these satellites provides images with certain specifications. Remote-sensing data are used for the purpose of detecting different types of geohazards of different scales, which is very useful for the identification, detection, classification, and mapping of geohazards [79]. In terms of landslide susceptibility assessment, remote-sensing data form the basis of the assessment, and entire data layers are added this layer.

DEM data: Individually, the DEM just includes information about the elevation variation in different areas, but using these data helps researchers to identify the morphology of the earth's surface and extract morphometric features using the differentiation of mountainous areas and plains, identification of contour concentration (slopes), differentiation between valleys and foothills, slope curvatures, slope gradients, topographic changes, etc. These features provide useful information about the types, scale, nature, and development of geohazards [80].

UAV images: UAVs were rapidly developed to characterize the different geohazard conditions on site by taking overlap images from the specific events and analyzing the failure conditions. UAVs provide real-time, rapid, ground-based surveys and detailed scale analyses of large damaged areas in different locations. The application of UAVs in landslide susceptibility assessment has extensively grown, and has become one of the most important tasks in site investigations [81].

Geological data: Geological maps are an unavoidable part of geohazard susceptibility analysis studies. Investigating the geological, tectonic, and seismic circumstances; the conditions of drainage patterns; the watershed status; and the location of the earthquakes, faults, etc., via efficient analysis is a priority in terms of evaluating and identifying disaster-prone and high-risk areas [3].

Ground surveys: The purpose of field investigations and ground surveys is to collect data (as much as possible) about the geohazard event. Visualization of different aspects and characteristics of the event is conducted, and the information about each influencing factor is then marked and digitized [8]. This survey utilized quite detailed information about landslides, which required an analysis of the evolution of disasters at different time stages, as well as of local sliding, the scale of the event, triggering factors, etc. [9].

Aerial images: Aerial photographs are the most common method for identifying and mapping the Earth's surface from low- to mid-distances; they are used to provide geological, topological, morphological, and tectonic maps [47]. Aerial images are useful for providing 1:5000 to 1:70,000 scale mapping, which is directly related to the geohazard scale and device specifications [79].

Historical events: Background checks of geohazards help to classify the different susceptible regions during a ground survey, which allows for the remote-sensing assessments to be completed. This completion provides a strong tool with which to distinguish high-risk from low-risk regions, especially in landslide events. In general, the occurrence of a landslide is a sign of future events due to the suitability of the area for slide occurrence [82].

This information is gathered for different types of geohazards, especially landslides, and categorized in a comprehensive database that represents historical events, as well as triggering factors and areas prone to sliding occurrences. The more complete the main database is in ANN-based analysis, the more precise its learning rate becomes, and the error rate is reduced significantly [83]. ANNs use the main database to generate training and testing datasets, which leads to learning and utilizing the predictive models. In the training set, the model learns to analyze, and in the testing set, the model is tested. The testing-to-training rate represents the capability of the model for learning, which is assessed according to the confusion matrix and evaluation criteria [73].

5. Landslide Susceptibility with ANNs

The utilization of ANNs in landslide susceptibility assessments is becoming popular due to their flexibility and capability to solve complicated problems with non-linear behaviors, as well as their measurable learning rates with specific errors [38]. Regarding the type, complexity, and expansion of the ANN models, predictive models provide high accuracy for prediction series with low errors.

Hecht-Nielsen [84], Aldrich et al. [85], and Kaastra and Boyd [86] found out that during the development of the ANN models in their studies, the ability to solve problems was directly related to the architecture of the ANNs (such as the number of neurons in the hidden layer), and this may not always be a simple process. Although several heuristic-based methods have been proposed to estimate the optimal number of neurons in the hidden layer, none of them have been recommended as universal guidelines. Fausett [87], in relation to the basics of the neural network, states that when the relationships between geohazard-triggering factors are complex or unknown, they will be useful in predicting the outcome. Additionally, ANNs have the ability to generalize in noisy environments, making ANN solutions more robust in the presence of incomplete or imprecise data [88]. Paola and Schowengerdt [89], in their research, attempted to use MLP-based back-propagation neural nets for the classification of multispectral remote sensing images. In this work, the authors provided the area sensitive to the reflectance of the satellite images in geohazard detection. Aleotti and Chowdhury [57] conducted a review study on landslide susceptibility assessment via different techniques before 1999, which revealed that the application of ANNs was able to consider more triggering factors during susceptibility analysis. Blonda et al. [90] used a regular MLP neural net, a two-stage hybrid (TSH) learning system, and an SAR intensity coherence image to detect erosion-exposed areas and landslide-prone regions. The results showed that the ANN models provided accurate results in terms of the detection of landslide-prone areas in the Sele and Ofanto river valleys, located in the Southern Apennines of Italy. Lee et al. [91], to analyze landslide susceptibility in two study areas of Yongin and Janghung, Korea, used new ANN-based predictive models which operated based on an extensive spatial database; they concluded that 14 different triggering factors were present. The results of the analysis were verified using the landslide location data. The validation results showed satisfactory agreement between the susceptibility map and the landslide location data. Elias and Bandis [92] proposed a fuzzy neural approach for landslide susceptibility mapping. Fuzzy linguistic rules were used to assign fuzzy membership values to different categories of thematic data layers, and the membership values were used to provide input neuron data for the ANN model. A single-output neuron with a value from 0 to 1 was considered to represent the degree of landslide susceptibility, which was confirmed based on real historical landslide data. A perceptron-type neural network was used for training, and a susceptibility map was prepared for the region. It was observed that the predictions of the ANNs were close to reality, indicating the satisfactory performance of the neural network model.

Lee et al. [93], in their study, used shallow learning procedures for susceptibility assessment of landslide occurrence. The results of the landslide susceptibility maps were compared and verified using known landslide locations in another area, Yongin, of Korea. According to the research contribution, it turned out that ANNs were an effective tool for analyzing landslide susceptibility. The same scholar and his colleagues focused on the main database and provided more information to complete the input data in other studies. The results can be used to reduce hazards associated with landslides and to plan land use and construction [94]. Lee et al. [95] used weighted ANNs to analyze landslide susceptibility as a useful tool for spatial data management and manipulation. A probability method was used to calculate the learning rate of each factor triggering landslide occurrence. The results of the study were used to develop an ANN-based landslide susceptibility index. Ermini et al. [96] applied MLP and the probabilistic neural network (PNN), from the shallow learning family, to landslide susceptibility in the Riomaggiore catchment, a subwatershed of the Reno River basin located in the Northern Apennines (Italy). The models were operated using 3342 records from 19 different input data sets. The results indicated that the ANNs provided appropriate landslide susceptibility mapping for the studied region. Gomez and Kavzoglu [97] and Ercanoglu [98], in different studies conducted in Venezuela and Turkey, applied MLP to landslide susceptibility analysis with various triggering factors, which led to suitable results. These studies found promising results for future studies in landslide susceptibility zonation. Lee and Evangelista [99] emphasized the significance of seismicity as a triggering factor for landslide occurrences, while Wang and Sassa [100] highlighted the influence of rainfall on landslides. In their respective studies, these authors utilized multilayer perceptron (MLP) models to map landslide susceptibility induced by earthquakes and rainfall in specific regions of interest. Nefeslioglu et al. [101], Melchiorre et al. [102], Yilmaz [103], and Kawabata and Bandibas [104] implemented comparative assessments by using different types of statistical, deterministic, and probabilistic ANNs methods to investigate the capability and performance of those methods regarding landslide susceptibility analysis. The results of these studies indicated that ANNs provided more reliable information for hazard mapping. Choi et al. [105], Chauhan et al. [106], Pradhan and Lee [107], and Yilmaz [108] conducted studies on cases from different countries based on the application of ANNs, which was verified by ground and benchmark algorithms. The results of these studies revealed that ANNs are capable of providing high accuracy in their results with a low rate of errors, which makes landslide susceptibility mapping and hazard risk predictions more reliable.

Kanungo et al. [109], Oh and Pardhan [110], Lee and Oh [111], Quan and Lee [112], Li et al. [113], Park et al. [114], and Nourani et al. [115] applied comparative assessments to predict the probability of landslide occurrence in mountainous regions, such as tropical areas, based on integrated benchmark classifiers and ANN techniques. The mutual concept of these scientific studies was related to completing the main database for training and testing sets, as well as increasing the types of benchmark learning, including the frequency ratio, logistic regression, adaptive neuro-fuzzy inference system (ANFIS), analytic hierarchy process, etc. Liu and Linzhi [116], Vasu and Lee [117], and Xiao et al. [118] attempted to use more complicated learning approaches for landslide susceptibility mapping, the results of which indicated significant improvements compared with regular benchmark classifiers (known as conventional machine learning (CML)) as well as shallow learning methods. Chen et al. [119] stated that the purpose of deep learning, which is considered one of the most important ANN techniques for predicting and classifying risk-prone areas, is to achieve more detailed results with considerable accuracy and the lowest error rates. Ortiz and Martínez-Graña [120], Wanf et al. [121], Ghorbanzadeh et al. [122], and Hajimoradlou [123] used CNNs for landslide susceptibility assessments, which led to the development of accurate susceptibility maps for landslides. The researchers indicated that the application of CNNs has a good impact on satellite images, and outputs can be converted into the GIS environment perfectly. Mutlu et al. [124] used RNNs for susceptibility assessments and the prediction of landslide-prone regions. The application of RNNs, in comparison with CNNs, is somewhat different in terms of accuracy and performance, but CNNs are adapted better. In several studies, Feng et al. [125], Yi et al. [126], and Pham et al. [127] employed CNNs to generate highly accurate susceptibility maps. The outcomes of these investigations demonstrated the effectiveness and potential of CNNs in landslide risk mapping. Azarafza et al. [63] proposed a highly accurate deep learning-based coupled CNN-DNN predictive model, which was verified by different benchmark learning algorithms. The researchers reached the highest rate of accuracy in their landslide susceptibility assessments. Ngo et al. [128] used DNN for national scale susceptibility assessments and predicted the areas prone to landslides. The results showed that the DNN, specifically, and the ANNs, generally, achieved excellent performances during susceptibility mappings of landslides. Nikoobakht et al. [12] mentioned using deep neural nets capable of solving complex conditions to study various triggering factors and uncertain variables in the database. Table 3 provides a brief description of several works conducted recently using ANN applications for landslide susceptibility assessment.

Table 3. A summary of recent developments in ANN application in the geo-engineering field.

No.	Author(s)/Year	Model	Triggering Factors	Accuracy (%)	Reference
1	Wang et al. (2023)	CNN	Human activities, geology, and material resources	86.4	[129]
2	Lui et al. (2023)	CML	Disaster prevention, disaster reduction and land use, resource management	89.1	[130]
3	Ikram et al. (2023)	COA, SailFish optimizer, MLP	DEM, aspect, slope angle, NDVI, distance to fault, plan curvature, profile curvature, rainfall, distance from river, distance to road, SPI, STI, TRI, TWI, land-use, and geology	79.7	[131]
4	Aslam et al. (2023)	CNN, ResNet	Seismicity, rainfall, slope angle, and unfavorable geological conditions	20.0	[132]
5	Wang et al. (2023)	CML	Lithology, DEM, curvature, slope angle, aspect, NDVI	95.3	[133]
6	Zhou et al. (2023)	AHP	Slope angle, slope aspect, curvature, relative relief, NDVI, distance from road, distance from river, distance from fault, lithology, landslide density points, land use	84.5	[134]
7	Dai et al. (2023)	Geographical random forest (GRF)	Spatial changes	86.0	[135]
8	Ma et al. (2023)	CF, DNN, CML	DEM, slope angle, aspect, undulation, curvature, watershed, distance from fault, distance from road	-	[136]
9	Tekin and Çan (2022)	MLP	Geology, DEM, slope angle, TWI, RI, profile curvatures, distance from faults and rivers	87.3–91.1	[137]
10	Zeng et al. (2022)	GNN net	Complex and heterogeneous geoenvironment	-	[138]
11	Selamat et al. (2022)	MLP	DEM, slope angle, aspect, curvature, TWI, distance to road, distance to river, lithology, rainfall	94.0	[139]
12	Renza et al. (2022)	CNN	Geology geomorphology, land use, rain, aspect, NDVI	88.0	[140]
13	Lucchese et al. (2021)	MLP	Lithology, slope angle, distance to stream, distance to road, SPI, DEM, curvature, slope angel, slope aspect	94.1	[141]
14	Al-Najjar et al. (2021)	GAN	DEM, slope angle, aspect, plan curvature, profile curvature, total curvature, lithology, land use, LULC, distance to road, distance to river, SPI, STI, TRI, TWI, NDVI	94.0	[142]
15	Tang et al. (2020)	MLP	Lithology, slope angle, distance to stream, distance to road, SPI, DEM, curvature, slope angle, slope aspect	-	[143]
16	Chen et al. (2020)	CML	DEM, slope angle, slope aspect, plan curvature, profile curvature, TWI, SPI, distance to faults, distance to river, lithology, hydrology	96.9	[144]
17	Bragagnolo et al. (2020)	MLP	DEM, aspect, slope, topographic moisture index, profile curvature, lithology, land-use	-	[145]
18	Moayedi et al. (2019)	MLP	DEM, slope aspect, land-use, plan curvature, profile curvature, soil type, distance to river, distance to road, distance to fault, rainfall, slope angle, SPI, TWI, lithology	76.7	[146]
19	Mandal et al. (2019)	MLP	DEM, slope aspect, slope angle, slope curvature, geology, soil, lineament density, distance to lineament, drainage density, distance to drainage, SPI, TWI, rainfall	81.5	[147]

The utilization of ANN methods for landslide susceptibility mapping offers several advantages, which can be categorized as follows:

- ○ Accounting for non-linear relationships: ANN methods are capable of capturing and modeling the complex, non-linear relationships between landslides and their causative factors. This enables a more comprehensive understanding of landslide susceptibility.
- ○ Accurate and adaptable output: ANN models provide accurate results that can be tailored to specific needs and requirements. They can be trained and fine-tuned to produce highly precise susceptibility maps.
- ○ Minimization of human error: By automating the computation process, ANN models minimize the possibility of human error. This enhances the reliability and consistency of the obtained results.
- ○ Reliable prediction accuracy: ANN methods have demonstrated the potential to achieve reliable prediction accuracies, contributing to more effective decision-making in landslide risk management.

However, it is important to acknowledge the limitations associated with ANN models, including:

- Algorithm selection challenges: With a wide range of algorithms available, selecting the most effective one for a specific application can be challenging. Careful consideration and evaluation are necessary in order to choose the most appropriate algorithm.
- High computational cost: Compared to other modeling approaches, ANN models can have high computational requirements. The training and processing of large datasets can be computationally demanding and time-consuming.
- Data intensity: ANN models heavily rely on the availability of comprehensive and quality datasets. The success of the model is contingent on the availability and suitability of the input data, which can pose challenges in data collection and preparation.

6. Challenges and Opportunities

According to the literature, neural network methods have been widely recognized for their ability to analyze, classify, and predict landslide susceptibility with low error rates and high accuracy, surpassing traditional methods in this regard. The precise susceptibility analysis facilitated by neural networks has significant implications on various aspects of research, including:

- Re-evaluation of development programs: Accurate landslide susceptibility analysis prompts a re-evaluation of existing development programs. This allows for informed decision-making and strategic planning to minimize the potential risks associated with landslides.
- Saving lives and property: By identifying areas prone to landslides through neural network-based susceptibility analysis, lives and property can be protected. This knowledge enables appropriate measures to be taken, such as evacuation plans or the implementation of protective structures.
- Damage reduction: The accurate identification of landslide-prone areas empowers authorities and stakeholders to implement preventive measures and engineering solutions that can significantly reduce the potential damage caused by landslides.
- Promoting appropriate urban development: Neural network-based analysis facilitates informed urban development by highlighting areas that are less susceptible to landslides. This knowledge aids in designing sustainable urban environments that prioritize safety and minimize the risk of landslides.
- Successful Infrastructure Design: Understanding landslide susceptibility allows for the incorporation of appropriate measures in infrastructure design, ensuring that structures can withstand potential landslide hazards. By avoiding sensitive regions or modifying facilities accordingly, the risk to infrastructure can be mitigated.

The use of neural network methods in landslide susceptibility analysis has proven to be instrumental in advancing these objectives, leading to improved safety, reduced damages, and more effective planning and development practices [148–151].

One of the important challenges regarding the reliability and the level of confidence of these neural networks is to what extent we can be sure of the landslide assessment results using this method. Now, the question is how we can obtain reliable results using this method. Increasing the ability to interpret data is a primary solution, while improving the data and reproducibility of these models is also needed in order to increase the output efficiency of the ANN nervous system. In addition to these, the generalization of data related to land hazards and the causes of landslides is one of the noteworthy points. Also, several hidden layers can be superimposed to create a shallow or deep neural network.

Other important challenges of ANN application are related to the input data and main database. All ANN systems need input data to operate, and the better, more quality, and more effective these data are, the more likely it becomes that the system will run correctly and we will see outputs with higher efficiency. However, the existence of a quality database is disrupted due to reasons such as the high cost and time-consuming nature of data collection, which prevents the proper functioning of the ANN system, and these disturbances will be eliminated by improving learning models from shallow to deep. Therefore, in order to achieve a more efficient and accurate performance of the system, firstly, a more suitable database should be used, and secondly, a significant portion of the data need to be cleaned, purified, and entered into the main database under supervision. Of course, this can be accomplished by combining the accessible data with relevant information to enrich the input database. Together, these methods will lead to the development of an outstanding and efficient database able to improve the learning rates of different ANNs. Nevertheless, there are still problems regarding landslide occurrence prevention and the lack of strategies to reduce these disaster impacts, which must be considered in urban development and planning.

Regardless of the challenges faced with landslide susceptibility analysis using ANNs, there are huge opportunities that come with the procedures. ANNs provide predictive models with measurable accuracy, helping to understand the learning rate and conditions. ANNs are capable of modifying coupled data changes based on the modeling aim, the sensitivity of the analysis, and the scale of the data. The analysis capability of big data and large databases provides ANNs with strong superiority compared to other knowledge-based methods. Also, ANNs, especially deep learning models, can operate with appropriate accuracy and low error rates when solving complicated problems.

Deep learning has emerged as a potent tool in the domain of riverside landslide susceptibility assessment, offering significant advancements in the analysis of geospatial data to identify and predict potential landslide-prone regions. Within the realm of machine learning, deep learning constitutes a subset characterized by the utilization of artificial neural networks to autonomously learn and extract intricate patterns and features from diverse and intricate datasets, encompassing remote sensing imagery, LiDAR data, and topographic information [59,63]. The paramount advantage of employing deep learning in landslide susceptibility assessment lies in its capacity to handle vast and heterogeneous datasets with remarkable efficacy. Conspicuously, CNNs excel at discerning and capturing spatial features from high-resolution remote sensing data, enabling the identification of subtle terrain variations and land cover nuances that serve as critical indicators of landslide-prone zones in riverside areas [69–71].

The application of deep learning in riverside landslide susceptibility assessment typically entails a series of interrelated steps. Commencing with data preprocessing, geospatial information is subjected to normalization, image cropping, and data augmentation to homogenize and optimize the input for neural networks. Subsequently, model training involves the deployment of a deep neural network, often in the form of a CNN, which is trained using labeled datasets comprising landslide occurrences and non-landslide areas. During this process, the network autonomously learns to extract salient features, forming representations that capture the relationships between the geospatial features and the likelihood of landslides. Once trained, the deep neural network is then applied to new, unlabeled data, facilitating predictions of landslide susceptibility and yielding landslide susceptibility maps [116–122]. These maps offer valuable insight for decision-makers, planners, and stakeholders in riverside communities, empowering them to prioritize risk mitigation strategies, implement timely and proactive early warning systems, and inform land use planning in regions deemed vulnerable to landslide hazards [6,9]. By virtue of its automated feature extraction capabilities and enhanced predictive accuracy, deep learning holds immense potential to revolutionize and elevate the field of riverside landslide susceptibility assessment, furthering our understanding of natural hazard dynamics and fostering resilient and sustainable development practices in high-risk regions.

According to the aforementioned points about the data and inputs to the system, the existence of landslide susceptibility assessments, and the incompleteness of information regarding predicting and measuring the probability of landslide occurrences and preventing financial and human losses, there is an increasing need to employ accurate methods with precise results. ANNs are reliable for avoiding errors and providing highly accurate susceptibility maps, making them one of the best ways to study landslides due to the advantages, capabilities, and diversity of neural networks.

7. United Nations Goals Exclusively Dedicated to Landslides

The United Nations (UN) has set a framework of 17 interconnected Sustainable Development Goals (SDGs) that address the most pressing global challenges. These goals, agreed upon by UN member states, aim to eradicate poverty; protect the planet; and ensure peace, prosperity, and well-being for all. The SDGs cover a wide range of issues, including poverty, hunger, health, education, gender equality, clean water and sanitation, affordable and clean energy, responsible consumption and production, climate action, and sustainable cities and communities, among others. The SDGs provide a blueprint for countries, organizations, and individuals to work together towards a more sustainable and equitable world. They recognize the interconnectedness of various social, economic, and environmental dimensions, understanding that progress in one area is dependent on progress in others. The goals emphasize the need for integrated approaches, partnerships, and collective action to address complex global challenges. The UN goals are designed to be transformative, seeking to leave no one behind and ensure that the benefits of development reach all segments of society, including the most vulnerable populations. They encourage countries to set their own national targets aligned with the SDGs, develop strategies for implementation, and monitor progress through indicators and reporting mechanisms. Figure 7 provides an overview of the UN SDGs [152].

While there are no specific SDGs exclusively dedicated to landslides, several goals indirectly address the issue. One such goal is Goal 1: No Poverty. Poverty reduction plays a crucial role in increasing the resilience of communities to natural hazards, including landslides. By addressing poverty, communities can gain improved access to resources, infrastructure, and services, which can contribute to better land-use planning, the development of safer housing, and the implementation of early-warning systems in landslide-prone areas. Goal 11: Sustainable Cities and Communities is also relevant. This goal emphasizes the importance of inclusive, safe, resilient, and sustainable cities. By enhancing urban planning, infrastructure development, and disaster risk reduction measures in landslide-prone areas, communities can reduce their vulnerability to landslides and ensure the safety and well-being of their residents.

Figure 7. An overview of UN SDGs (adapted from Ref. [148]).

Goal 13: Climate Action is another SDG that indirectly relates to landslide risk reduction. Climate change can significantly impact landslide occurrences through changes in rainfall patterns, increased weather extremes, and other environmental factors. By addressing climate change and implementing mitigation and adaptation measures, communities can reduce the susceptibility to and impacts of landslides. Efforts to promote sustainable land management practices, preserve natural landscapes, and conserve forests also align with Goal 15: Life on Land. These actions help to mitigate landslide risks by maintaining the stability of slopes, reducing erosion, and protecting biodiversity. By focusing on sustainable land use practices and ecosystem preservation, communities can enhance their resilience to landslides and promote the long-term health of terrestrial ecosystems.

It is important to note that the SDGs provide a broad framework for global development, and while landslides may not be explicitly mentioned, the goals indirectly support efforts to address landslide risk reduction through sustainable development practices, climate action, and disaster risk reduction strategies. These goals recognize the interconnectedness between environmental sustainability, poverty reduction, urban planning, and climate change mitigation and adaptation. They encourage countries, organizations, and communities to work towards inclusive and sustainable development, considering the potential impacts of natural hazards such as landslides. While there may have been updates or developments in UN initiatives related to landslides beyond our knowledge cutoff, the SDGs provide a foundation for promoting actions that contribute to reducing landslide risks and enhancing overall resilience to natural disasters.

8. Conclusions

In conclusion, this paper provides a comprehensive overview of the application of artificial neural networks (ANNs) in landslide susceptibility assessments, considering the goals set forth by the United Nations. The study explores the hazards and triggering factors associated with landslides, such as slope steepness, soil characteristics, precipitation patterns, and land cover changes. Understanding these factors is crucial for accurate assessment of landslide susceptibility and mitigating the risks which landslides pose to human lives and infrastructure.

The paper discusses various susceptibility assessment classifications, including qualitative, quantitative, and semi-quantitative approaches. While these methods have their merits, they also have limitations in terms of accurately capturing the complexity of landslide susceptibility. This motivates the exploration of ANNs as an alternative approach.

ANNs are intelligent computational methods inspired by the functioning of the human brain, and are capable of learning and recognizing patterns in large datasets. They can integrate multiple conditioning factors and capture nonlinear relationships, making them well-suited for landslide susceptibility analysis. The study highlights the different types of ANNs commonly employed in landslide susceptibility assessments, including shallow learning models like multilayer perceptrons (MLPs) and more advanced deep learning models like deep neural networks (DNNs) and convolutional neural networks (CNNs). Deep learning models, in particular, have shown superior performance in capturing complex patterns and identifying critical factors contributing to landslide susceptibility. By leveraging the power of ANNs, researchers and practitioners can enhance the accuracy and precision of landslide susceptibility maps and models, enabling more effective decision-making and risk reduction strategies.

Aligned with the goals of the United Nations, employing ANNs in landslide susceptibility analyses promotes sustainable development, resilience, and disaster risk reduction. By accurately assessing landslide susceptibility, decision makers can develop appropriate land-use planning, infrastructure design, and early-warning systems to protect vulnerable communities. The application of ANNs also contributes to Goal 11: Sustainable Cities and Communities, as it helps in creating safe, inclusive, and resilient urban environments. Moreover, advancements in ANN-based methods should continue to address challenges such as data availability, model interpretability, and uncertainty quantification while exploring new opportunities to enhance the effectiveness of landslide susceptibility assessments. In conclusion, the integration of ANNs in landslide susceptibility assessments offers promising avenues for improving our understanding of landslide dynamics and enhancing risk management strategies. By considering the goals of the United Nations, this research contributes to the broader agenda of sustainable development, resilience-building, and ensuring the safety and well-being of communities in landslide-prone areas. Continued research and innovation in this field will further advance our capability to accurately predict and mitigate the impacts of riverside landslides.

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Abbreviations

UN	United Nations
SDGs	Sustainable Development Goals
UN SDGs	United Nations' Sustainable Development Goals
ANNs	Artificial Neural Networks
GIS	Geographic Information System
DEM	Digital Elevation Model
CRU	Climatic Research Unit
LULC	Land-use and Land-cover
ML	Machine Learning
SAR	Synthetic Aperture Radar
CNNs	Convolutional Neural Networks
InSAR	Interferometric Synthetic Aperture Radar
RNN	Recurrent Neural Networks

DNN	Deep Neural Networks
LSTM	Long Short-Term Memory
DFNs	Deep Belief Nets
AEs	Autoencoders
DAN	Generative Adversarial Nets
GNN	Graph Neural Nets
UAVs	Unmanned Aerial Vehicles
PNN	Probabilistic Neural Network
MLP	Multilayer Perceptrons
CML	Conventional Machine Learning
ANFIS	Adaptive Neuro Fuzzy Inference System

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